IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received May 8, 2019, accepted June 9, 2019, date of publication June 19, 2019, date of current version July 11, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2923791

Maintenance Decision-Making Support for Textile Machines: A Knowledge-Based Approach Using Fuzzy Logic and Vibration Monitoring

MARIUS BĂBAN[1], CĂLIN FLORIN BĂBAN[1], AND MARIUS DARIUS ŞUTEU[2]
[1]Faculty of Management and Technological Engineering, University of Oradea, 410087 Oradea, Romania
[2]Faculty of Energy Engineering and Industrial Management, University of Oradea, 410087 Oradea, Romania
Corresponding author: Călin Florin Băban (cbaban@uoradea.ro)

ABSTRACT A condition-based maintenance approach may be used for planning the maintenance activities of textile machines with a satisfactory performance by developing maintenance decision-making support based on fuzzy logic and vibration monitoring. Since textile machines are systems with moving parts operating at relatively high-speed, vibration monitoring was used to indicate their failure development. At the same time, the characterization of the degradation phenomenon of textile machines involves some degree of uncertainty and vagueness. Within this context, a knowledge-based approach that employed fuzzy logic and vibration monitoring was developed. Deterioration symptoms do announce future failures of industrial machines, therefore building a maintenance decision-making support for scheduling maintenance actions of textile machines based on the estimation of their condition becomes a resourceful way to prevent their further deterioration.

INDEX TERMS Condition-based maintenance, vibration monitoring, fuzzy logic, maintenance decision-making.

I. INTRODUCTION

The structure of industrial machines that integrates heterogeneous components and complex subsystems, is becoming increasingly advanced and difficult to be controlled [1]. Moreover, such machines often can fail, which has an important influence on their availability and consequently on the productivity of manufacturing facilities [2]. As a result, manufacturing companies should consider any potential characteristic that can improve the effectiveness of their machines. Among such features, maintainability is considered to have an important influence on the system's effectiveness [3], [4], thus enabling any company to become a world-class manufacturer [5], [6]. Maintainability has been defined as the feature of a machine to maintain or restore its prescribed functions in the shortest possible time [7]. Therefore, maintainability depends on how failures are identified as well as on how maintenance activities are planned and carried out in order to prevent or eliminate the deterioration of machines.

Several strategies have shaped the field of maintenance activities that can be broadly classified in reactive and proactive strategies [8]. One of the simplest strategies is corrective maintenance, a reactive approach in which maintenance actions are performed to restore the designated functions of machines only after their failure [8], [9]. At the same time, production losses and maintenance costs related to this strategy are usually high [10]. To respond to these drawbacks, proactive maintenance strategies have been developed. Since such strategies involve planned maintenance actions before the failure of machines [8], the maintenance activities are most of the time implemented in a more cost-effective way compared with corrective maintenance [11].

Preventive and predictive maintenance are the main types of proactive maintenance strategies [8], [12] and their employment in industry has been presented in existing literature [1], [13]. In preventive maintenance strategies, the maintenance actions are carried out after a pre-specified time, so they are also known as maintenance on a scheduled basis. Block replacement policy and age replacement policy are classical approaches in preventive maintenance [14]. Several criteria may be employed in designing the preventive maintenance policies. Such criteria are either maximization of the machine availability or minimization of its average maintenance cost [14]. Regardless the type of preventive

The associate editor coordinating the review of this manuscript and approving it for publication was Ming Luo.

maintenance policies, specification of the scheduled times at which maintenance activities should be performed requires adoption of distribution law associated with failure mechanisms of the analyzed machine [15]. The adoption of the distribution law is based on the times-to-failure of the machine under consideration, which demands a rigorous system of collecting and recording its failure data [16], [17]. However, this is mostly not the case for textile machines so that the lack of sources of their failure data makes difficult to formulate the preventive maintenance policies.

Nevertheless, the failure of machines is most of the time preceded by some non-specific malfunction or deterioration symptoms [18]. Therefore, a condition-based maintenance approach, which is a predictive strategy, may be used for planning the maintenance activities of machines. In general, a condition-based maintenance approach is based on the condition monitoring of the machine and on the process of decision-making for its maintenance [19, p. 522]. Initially, the technical state of the machine is estimated through condition monitoring using various sensors. Then, it is followed by a decision regarding the maintenance strategy that should be carried out considering its operating conditions [19]. The continuous development of the industrial sensors that are able to capture different degradation signals and the rapid advances in both hardware for data acquisition and software for signal processing have accelerated the implementation of condition-based maintenance [20]–[22].

Numerous industrial applications of condition-based maintenance have been reported in recent literature [16], [23]–[25]. Nevertheless, its employment in the field of textile machines is relatively undeveloped and it is mainly dedicated to condition monitoring. Sharp [26] presented a system for condition monitoring of the needles of high-speed knitting machines, based on transducers capable of monitoring the cam-needle reactive forces. Cloppenburg et al. [27] also highlighted the employment of sensor systems in developing condition monitoring of manufacturing machines for textiles. Wolfram and Isermann [28] described a method based on telediagnosis, which used advanced communication channels to monitor a textile machine for fault detection and diagnosis of its individual parts. Scarpellini *et al.* [29] depicted a Web-based application to monitor the condition state of textile machines, which also provide the possibility of conducting the analysis of the collected data regarding their productivity and efficiency. It can, therefore, be noticed that there is scarce research investigating the development of decision-making support in condition-based maintenance of textile machines.

Within this context, this article aims to provide a maintenance decision-making support for failure detection of textile machines based on the available condition monitoring data. The remainder of the paper is structured as follows: the next section describes a framework for maintenance decision-making support for textile machines taking the existing research into account. The following section presents results and discussion of the application of the developed maintenance decision-making support for a high-speed overlock sewing machine. Finally, the last section concludes with a summary of findings and future research recommendation, respectively.

II. DEVELOPMENT OF A MAINTENANCE DECISION-MAKING SUPPORT FRAMEWORK FOR TEXTILE MACHINES

In the condition-based maintenance strategy, the maintenance activities are performed only when they are needed [30]. According to Jardine *et al.* [22, p. 1484], implementation of condition-based maintenance involves three major steps: acquisition of data, followed by their analysis and a maintenance decision process at the end. In the first step, relevant data to the state of machines have to be acquired through a data acquisition facility. Next, the collected data are processed and analyzed to be better interpreted. An appropriate maintenance decision is adopted in the third step. This paper addresses the development of a framework for maintenance decision-making support for textile machines, considering the approach introduced by Jardine *et al.* [22]. The proposed framework is depicted in Figure 1 and its features are detailed below.

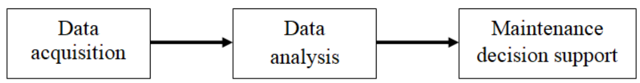


FIGURE 1. Maintenance decision-making support framework (adapted from [22], p. 1484).

A. DATA ACQUISITION THROUGH VIBRATION MONITORING

With the rapid advancement of data acquisition technologies and systems, collecting data has become more affordable and achievable [22]. Therefore, the relevant data regarding the state of machines can be collected through monitoring different parameters. However, the approaches for detection of the state of machines have no universal application and specific methods have to be employed, accordingly to the characteristics of the monitored machines. Vibration monitoring, acoustic monitoring, oil or wear particle analysis, temperature monitoring or electrical monitoring are among the most used methods [16], [21], [31].

Industrial machines, which integrate moving parts inevitably generate some levels of vibrations in their operations. At the same time, any abnormal change in the level of vibrations of the machine structural components may indicate the development of a fault. Therefore, vibration monitoring has become a main approach in revealing the running condition of the machines and detecting their faults in the incipient states [32]. Moreover, because of rapid data collection and relatively easy interpretation, it is one of the most effective techniques for monitoring the condition of machines and equipment [33]. The impact of vibration-based maintenance on production and quality was described in [3]. Al-Najjar [3] also highlighted the possible return on the investments that support the cost of buying and maintain such technology, as well as the training of personnel for its employment. Therefore, vibration monitoring is considered well suited for mechanical systems such as industrial machines and equipment [30], [34].

This is the case of textile machines, which are systems with rotating and reciprocating components operating at relatively high-speed regimes. Since vibration sensors can be mounted on different critical components of textile machines, vibration monitoring systems can be used in detecting their failure development. Therefore, a vibration monitoring approach is employed to monitor the state of textile machines. Various vibration transducers are now available such as displacement transducers, velocity transducers, accelerometers or laser Doppler vibrometers [33]. Since piezoelectric accelerometers are by far the most commonly used in machine condition monitoring [31], they are also adopted for textile machines.

On the other hand, an increased level of vibrations can often generates effects such as the breaking of thread and damage of needles, and the shutdown of the machine. Moreover, the manufacturers of textile machines do not provide the admissible level of vibrations during the operation of their machines. Şuteu *et al.* [35] employed vibration monitoring to establish the operating speed of the textile machines, but their results were based on an empirical approach. At the same time,the relationship between vibrations and speed of textile machines is expected to be a complex curvilinear one. Since spline functions are recognized to be appropriate for modeling such relationships, a spline regression could be employed to represent the relationship between the amplitude of vibrations (A) and speed of textile machines (v_t) as follows [36, p. 552]:

$$A(v_t) = \sum_{i=0}^{n} \beta_{0i} v_t^i + \sum_{k=1}^{K} \beta_{kn} (v_t - \xi_k)_+^n \tag{1}$$

where β_{0i}, $i = \overline{1 \ldots n}$ and β_{kn}, $k = \overline{1 \ldots K}$ are the regression parameters of the n*th* degree spline function and K its knots, while

$$(v_t - \xi_k)_+ = \begin{cases} 0, & v_t \le \xi_k \\ v_t - \xi_k, & v_t > \xi_k. \end{cases}$$

Thus, the following are concluded:

Proposition 1: A vibration monitoring approach is proposed in order to monitor the state of textile machines.

Proposition 2: Vibration monitoring is proposed in order to recommend the operating speed of the textile machines corresponding to a level as low as possible of vibrations.

B. DATA ANALYSIS

Jardine *et al.* [22, p. 1486] classified collected data through data acquisition step into three types, respectively value data, waveform data, and multidimensional data. Value data are represented by a single value, such as the temperature. Waveform data exist in time series such as vibration data, while examples of multidimensional data are image data, such as infrared thermograms. These data can be analyzed using different algorithms and techniques and their employment highly depends on the types of previously collected data. Such algorithms and techniques were also discussed in [22], with a more detailed consideration of waveform data. In practice, the analysis of value data is considered to be easier compared with the waveform or multidimensional data analysis [16].

Therefore, the next step after data collection based on the monitoring approach presented in section II.A is the analysis of vibration signals. Various methods are available for this purpose, including the analysis of time-domain features, frequency-domain features and time–frequency features [22], [34]. These three main categories of signal processing were also reviewed by Jardine *et al.* [22]. Considering the advantage of the frequency-domain analysis to easily detect the location of the fault, this signal processing technique is employed for textile machines. At the same time, the time–frequency analysis may be used to reveal changes in the frequency contents of the signal over time.

Thus, this leads to conclude the following:

Proposition 3: The frequency-domain and time–frequency analysis are proposed to detect the fault of textile machines.

C. MAINTENANCE DECISION-MAKING SUPPORT FOR TEXTILE MACHINES: A FUZZY LOGIC APPROACH

Different approaches are available to support maintenance decision making [24], [37]–[39]. In general, these approaches can be grouped into physical-based approach and data-driven approach [39]. According to Peng *et al.* [24], a physical-based approach is usually built on mathematical models related to physical processes that influence the degradation of the system of interest. The physical-based models are considered more accurate and precise comparing with the data-driven ones [38]. However, the development of such models is more difficult, computationally intensive and time-consuming, and their practical applications are generally system-specific [38]. For such reasons, a data-driven approach is more widely employed as a support for decision making in condition-based maintenance than a physics-based one.

A data-driven approach is based on a model that correlates various monitored parameters (such as vibration, acoustic emission, temperature, etc.) of the analyzed system to its degradation [38]. For this aim, both statistical and artificial intelligence techniques are available to develop the model, which is then used as a maintenance decision-making support [22], [24], [38]. The statistical analysis employs, among other techniques, multivariate statistical methods, regression models or different state space models [22], [24]. Artificial intelligence analysis is mainly based on techniques from soft computing, such as fuzzy logic, neural networks, evolutionary algorithms or their combination [22], [38]. Considering their capacity to deal with the complex aspects of decision making that are normally associated with human intelligence, soft computing techniques are becoming more and more used in the maintenance decision- making [38].

Since the degradation phenomenon of textile machines is a nonlinear and complex process that is influenced by various factors, it is difficult to accurately determine a mathematical representation of this process. Therefore, the degradation phenomenon of textile machines is characterized by some degree of uncertainty and vagueness. On the other hand, a data-driven model based on monitoring the state of textile machines can be affected by some inaccuracy and imprecision due to the limitations arising from the condition monitoring process [25]. Moreover, well-qualified experts are required to convert existing data into useful information for maintenance decision making, and they are not so often available [40].

Within this context, a knowledge-based approach based on fuzzy logic may be employed to overcome such difficulties. Fuzzy logic has been employed in fault diagnosis of different systems such as rotating machines [41]–[43], printing machines [44], railway wheels [45], pumps [46] or gearboxes [47]. It has also been employed to predict fault severity in helical gearboxes [48] or to develop an early warning system for improving decision-making in condition-based maintenance [49].

Several studies depicted the employment of soft computing and particularly of fuzzy logic in various fields of textile machines [50]–[53]. However, the use of fuzzy logic in the condition-based maintenance of textile machines is by far less investigated. Hence, an approach based on fuzzy logic and vibration monitoring has been developed considering the decision-making process presented in [54], as follows:

1) Set up the extracted features from the signal processing analysis in section II.B $X_V = \{x_1, x_2, \ldots, x_N\}$ as the input linguistic variables in the fuzzy decision system.

2) Define the domain values for each input linguistic variable $x_i, i = \overline{1, N}$:

$$x_i : D_{x_i} = [L_{x_i}^{inf}, L_{x_i}^{sup}], \quad i = \overline{1, N} \tag{2}$$

where $D_{x_i} = [L_{x_i}^{inf}, L_{x_i}^{sup}]$ is the tolerance interval of each x_i , $i = \overline{1, N}$.

3) Define the linguistic terms $LT_i^{X_V}$ related to each linguistic variable $x_i, i = \overline{1, N}$:

$$x_i : LT_i^{X_V} = \left\{LT_{i1}^{X_V}, LT_{i2}^{X_V}, \ldots, LT_{in_i}^{X_V}\right\}, \quad i = \overline{1, N} \tag{3}$$

where n_i is the number of linguistic terms of the x_i input linguistic variable ($i = \overline{1, N}$).

4) Establish the membership functions $MF_i^{X_V}$, $i = \overline{1, N}$ associated with each linguistic term $LT_i^{X_V}$, $i = \overline{1, N}$ in the expression (3):

$$x_i \rightarrow LT_i^{X_V} \rightarrow MF_i^{X_V} = \left\{mf_{i1}^{X_V}, mf_{i2}^{X_V}, \ldots, mf_{in_i}^{X_V}\right\}, \quad i = \overline{1, N} \tag{4}$$

The membership functions in relation (4) may be chosen among the available membership functions presented in the literature [55].

5) Set up the measure used for maintenance scheduling as the output linguistic variable of the fuzzy decision system. Let y_C be the output linguistic variable of the fuzzy decision system.

6) Define the domain value for the output linguistic variable y_C:

$$y_C : D_{y_C} = [L_{y_C}^{inf}, L_{y_C}^{sup}] \tag{5}$$

where $D_{y_C} = [L_{y_C}^{inf}, L_{y_C}^{sup}]$ is the tolerance interval of the output y_C.

7) Define linguistic terms LT^{y_C} related to the linguistic variable y_C:

$$y_C : LT^{y_C} = \left\{ LT_1^{y_C}, LT_2^{y_C}, \ldots, LT_{n_M}^{y_C} \right\} \tag{6}$$

where n_M is the number of linguistic terms of the output linguistic variable y_C.

8) Establish the membership functions MF^{y_C} associated with the linguistic terms of relation (6)

$$y_C \rightarrow LT^{y_C} \rightarrow MF^{y_C} = \left\{mf_1^{y_C}, mf_2^{y_C}, \ldots, mf_{n_M}^{y_C}\right\} \tag{7}$$

The membership functions in relation (7) may be chosen among the available membership functions presented in the literature [55].

9) Set up the fuzzy rules base and the fuzzy inference rules

$$\begin{aligned}&FIR_r :\\ &IF(x_1 = LT_{1j_1}^{X_V} AND \ldots x_i = LT_{iji}^{X_V} \ldots AND x_N = LT_{Nj_N}^{X_V})\\ &THEN(y_C = LT_p^{y_C})\end{aligned} \tag{8}$$

In relation (8), $r = \overline{1, n_R}$ and n_R represent the number of fuzzy inference rules, while $j_1 = \overline{1, n_1}, j_i = \overline{1, n_i}, j_N = \overline{1, n_N}$ and $p = \overline{1, n_M}$.

10) Establish the defuzzification method

Among the available methods, the centroid method is by far most frequently used because of its robustness and less sensitivity to changes [56], and was proposed for defuzzification.

Thus, the following is concluded:

Proposition 4: Considering the measured values of the X_V *at one moment* t_i *as* $X_{V_{t_i}} = \{x_{1_{t_i}}, x_{2_{t_i}}, \ldots, x_{N_{t_i}}\}$, *the value of* $y_{C_{t_i}}$ *is obtained through the fuzzy decision system. If* $y_{C_{t_i}} \in D_{y_C}$ *the textile machine is considered in a good state and usable. Otherwise, it is considered in a failure state and maintenance actions are needed.*

III. RESULTS AND DISCUSSION

An illustrative example of the application of the maintenance decision-making support framework developed in the previous section is shown next for an overlock sewing machine. The analyzed textile machine uses two needles and can reach high speeds. According to its manufacturer, it is 35% to 100% faster than a normal one. The experiments have been conducted on cotton using Nm 80 needles.

Since the condition of the needles has a major influence on fabric quality [26], the experiments were carried out using both new and defective needles. Textile samples have been stitched with both new and defective needles. For each sample, the abrasion resistance in the stitched area has been

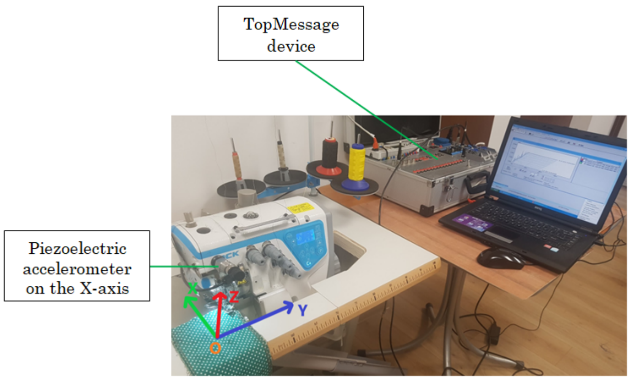


FIGURE 2. The data acquisition system for vibrations measurement along with the X-axis of a Cartesian coordinate system (X, Y, Z).

determined through a Martindale abrasion tester [57], which is used to assess the moment of occurrence of a defect in the stitched area (expressed by the number of Martindale cycles until the defect occurs).

A. DATA COLLECTION

Vibration monitoring was employed to indicate the technical state of the overlock sewing machine. The condition monitoring process was based on a data acquisition system composed of an accelerometer sensor, TopMessage device, and a personal computer. Vibrations were individually measured along with the X-axis, Y-axis, and Z-axis of a Cartesian coordinate system (X, Y, Z) using a piezoelectric accelerometer on each axis. The Vibrolab software was used for the analysis of vibration signals. Figure 2 depicts the data acquisition system for the measurement of vibrations along with the X-axis.

The sensitivity of the piezoelectric accelerometer was 100 mV/g $\pm$ 5%. For both the TopMessage device and accelerometer piezoelectric, a calibration has been performed before their employment. The noise or external perturbations outside the bandpass of the monitored signal have been removed with a high-pass filter and a low-pass filter that were set at 10 Hz and 1000 Hz, respectively. The Vibrolab software was used to obtain the amplitude of vibrations that had been expressed using the root-mean-square (rms) velocity (mm/s rms).

B. DATA ANALYSIS

Operating at high speed the overlock sewing machine generates vibrations that above some levels may cause the occurrence of various defects on the sewed fabrics: uneven tension of the stitches, sewing thread breakage, wrinkled stitches, etc. Therefore, considering vibration monitoring, it is possible to establish an operating regime at which the vibrations are at their lowest values. Table 1 presents the amplitude of vibrations measured along with the X-axis, Y-axis, and Z-axis for a new needle at different operating regimes.

A spline regression as expressed in relation (1) was used to model the dependency between the amplitude of vibrations

TABLE 1. The measured amplitude of vibrations at different operating regimes of the overlock sewing machine.

Operating regime v_t (stitches/minute)	Measure amplitude of vibrations (mm/s rms) X-axis $(A_x)_m$	Y-axis $(A_y)_m$	Z-axis $(A_z)_m$
1500	215.18	49.01	26.54
2000	154.14	25.85	22.26
2500	159.14	9.96	15.89
2600	145.11	7.81	16.28
2700	166.83	10.59	21.99
2800	166.62	12.45	24.20
3000	176.61	56.79	26.96
3500	192.14	94.69	37.88
4000	221.34	108.67	40.06
4500	248.45	124.04	78.66
5000	246.83	129.37	79.94

and speed of the analyzed textile machines. The R software was employed to perform all computations of the spline regression modeling [58], which is described next for the dependency $A_x(v_t)$. First, this dependency is represented graphically and based on the data representation, a cubic spline function ($n = 3$) is considered to represent $A_x(v_t)$. Next, the analysis is conducted for $K = 0$ (no knots), $K = 1$ (1 knot automated placed at the median of v_t), $K = 2$ (two knots automated placed at the two tertiles points of v_t) and $K = 3$ (three knots automated placed at the first, second and third quartile of v_t). Figure 3 illustrates the cubic spline regression models for the $K = \overline{0, 3}$ knots, along with the initial data.

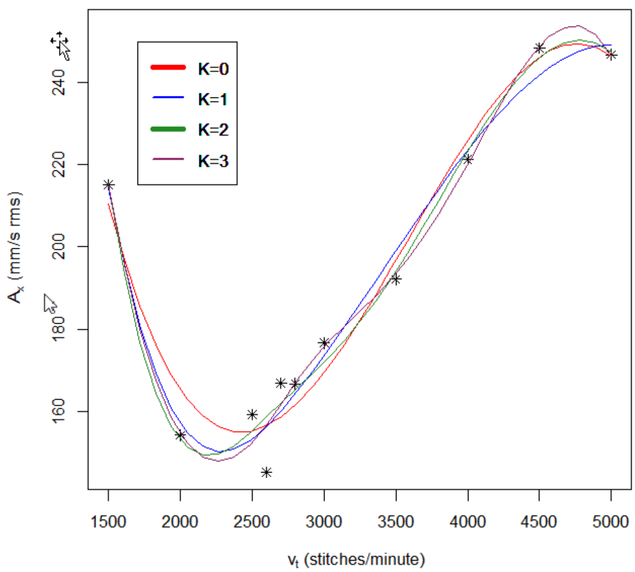
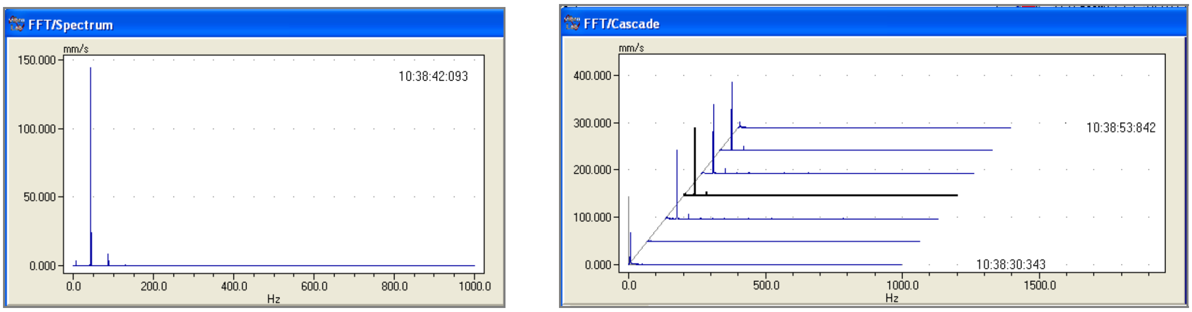


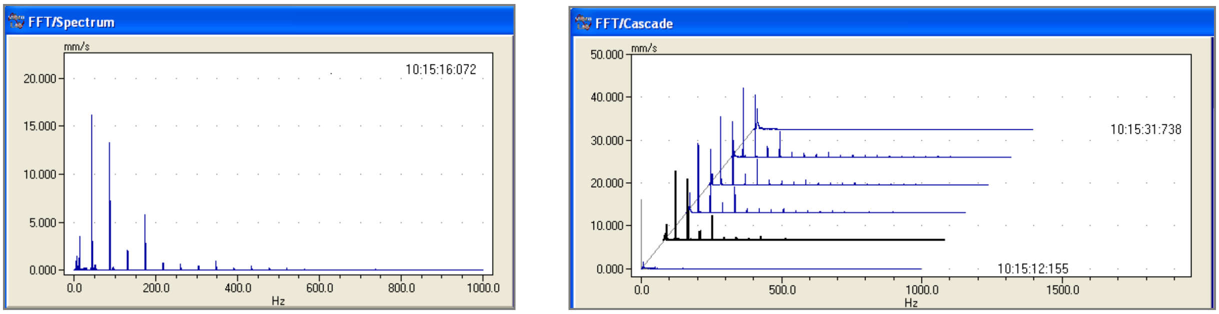
FIGURE 3. The cubic spline regressions.

The values of the multiple R-squared for each cubic spline regression are presented in Table 2.



a) b)

FIGURE 4. **The values of the amplitude of vibrations at the recommended operating regime for a new needle along with the X-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**



a) b)

FIGURE 5. **The values of the amplitude of vibrations at the recommended operating regime for a new needle along with the Y-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**

TABLE 2. **The multiple R-squared for the cubic spline regression ($A_x(v_t)$).**

Knots of the cubic spline regression	K=0	K=1	K=2	K=3
Multiple R-squared	0.965	0.9761	0.9813	0.9848

Considering the data in Table 2, the cubic spline regression with K = 3 knots has been employed to model the dependency $A_x(v_t)$, which can be written as:

$$\begin{aligned} A_x(v_t) = \ & 993.8223 - 9.171375e - 01^* v_t \\ & + 3.150107e - 04 * v_t^2 - 3.311994e - 08^* v_t^3 \\ & - 9.688592e - 08^*(v_t - 2550)_+^3 \\ & + 1.56793e - 07^*(v_t - 2800)_+^3 \\ & - 7.239858e - 08^*(v_t - 3750)_+^3 \end{aligned} \tag{9}$$

The minimum value of the expression (9) in the interval (1500, 5000) was obtained at $v_t = 2264.319$ stitches/minute and was equal to 147.7291 mm/s rms. Nevertheless, the speed of the analyzed textile machine can be set with a step of 100 stitches/minute, so that the minimum set value of A_x resulted equal to 147.8422 mm/s rms at $v_t = 2300$ stitches/minute.

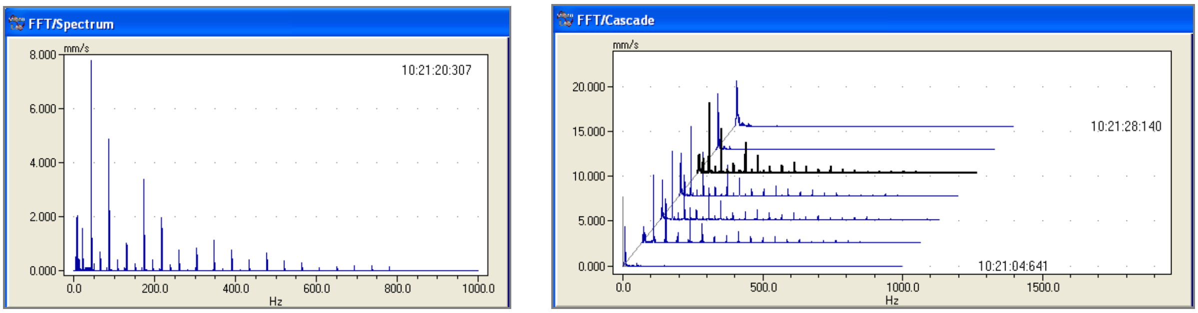
A similar approach was conducted for the dependencies $A_y(v_t)$ and $A_z(v_t)$, respectively and the results are shown in Table 3.

TABLE 3. **The results of the cubic spline regression modeling of $A_y(v_t)$ and $A_z(v_t)$.**

Knots of the cubic spline regression	Multiple R-squared		Minimum computed value of amplitude of vibrations/speed (mm/s rms - stitches/ minute)		Minimum set value of amplitude of vibrations/speed (mm/s rms– stitches/ minute)	
	$A_y(v_t)$	$A_z(v_t)$	$\left(\frac{A_y}{v_{t_y}}\right)_c$	$\left(\frac{A_z}{v_{t_z}}\right)_c$	$\left(\frac{A_y}{v_t}\right)_s$	$\left(\frac{A_z}{v_t}\right)_s$
K=0	0.9435	0.9418	-	-	-	-
K=1	0.9436	0.9435	-	-	-	-
K=2	0.9848	0.9461	6.4856/ 2471.57	-	6.5886/ 2500	-
K=3	0.9821	0.9789	-	13.6586 / 2411.09	-	13.6686 / 2400

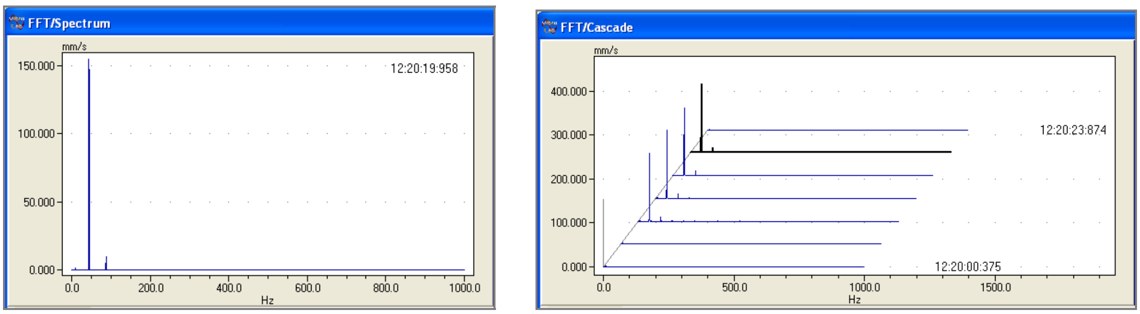
A comparison between the minimum measured and minimum set values of amplitude of vibrations /speed is depicted in Table 4. Since the amplitudes of vibrations along with the X-axis have much higher values than along with the Y-axis and Z-axis, the recommended operating regime for the overlock sewing machine was 2600 stitches/minute.

The values of the of vibration amplitudes in both frequency-domain (FFT) and time–frequency (FFT/Cascade) at the recommended operating regime and a new needle are shown in Figure 4 (along with the X-axis), Figure 5 (along with the Y-axis) and Figure 6 (along with the Z-axis).



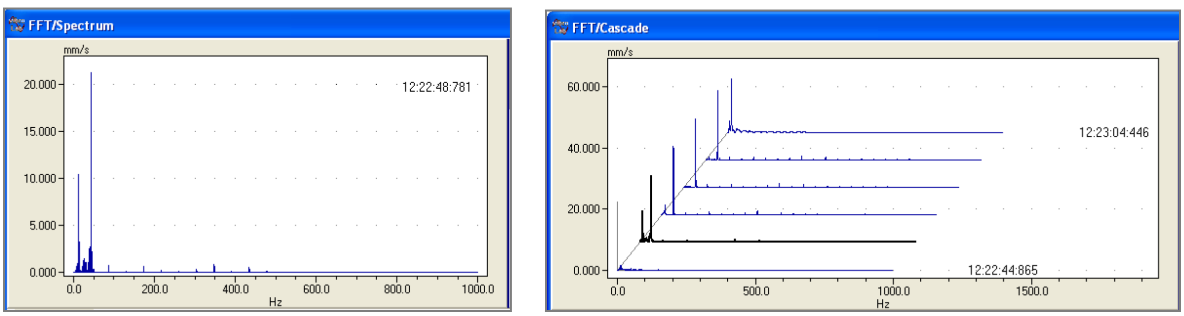
a) b)

FIGURE 6. **The values of the amplitude of vibrations at the recommended operating regime for a new needle along with the Z-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**



a) b)

FIGURE 7. **The values of the amplitude of vibrations at the recommended operating regime for a defective needle along with the X-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**



a) b)

FIGURE 8. **The values of the amplitude of vibrations at the recommended operating regime for a defective needle along with the Y-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**

TABLE 4. **The minimum measured and set values of amplitude of vibrations.**

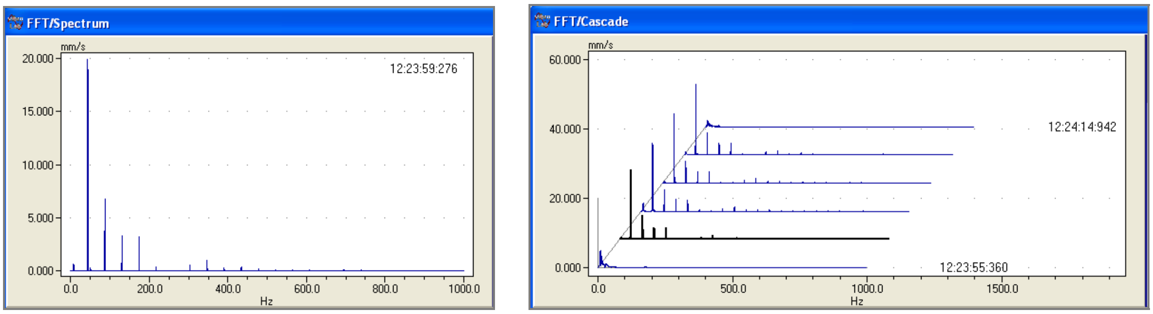
	Amplitude of vibrations/speed (mm/s rms - stitches/minute)		
	A_x / v_t	A_x / v_t	A_x / v_t
Minimum measured	145.11/2600	7.81/2600	15.89/2500
Minimum set	147.8422/2300	6.5886/2500	13.6686/2400

Summarizing, for a recommended operating regime of 2600 stitches/minute and a new needle, the amplitude of vibrations of the analyzed machine are 145.11 mm/s rms for the X-axis, 7.81 mm/s rms for Y-axis and 16.28 mm/s rms Z-axis.

Similarly, the values of the of vibration amplitudes in both frequency-domain (FFT) and time–frequency (FFT/Cascade) at the recommended operating regime and a defective needle are presented in Figure 7 (along with the X-axis), Figure 8 (along with the Y-axis) and Figure 9 (along with the Z-axis). To sum up, for a recommended operating regime of 2600 stitches/minute and a defective needle, the amplitude of vibrations of the analyzed machine are 155.76 mm/s rms for the X-axis, 20.05 mm/s rms for Y-axis and 22.47 mm/s rms Z-axis.

C. THE DECISION-MAKING PROCESS

Next is presented the employment of the approach based on fuzzy logic and vibration monitoring for the maintenance



a) b)

FIGURE 9. **The values of the amplitude of vibrations at the recommended operating regime for a defective needle along with the Z-axis: a) frequency-domain (FFT); b) time–frequency (FFT/Cascade).**

decision process of the overlock sewing machine. The amplitude of vibrations measured along with the X-axis, Y-axis and Z-axis were used as the input linguistic variables $X_V = \{A_X, A_Y, A_Z\}$. The abrasion resistance of the textile fabric sample using the Martindale abrasion tester was used as output linguistic variable y_c = ARM. Table 5 shows the domain values and the linguistic terms associated with each input variable and the output linguistic variable, respectively.

TABLE 5. **The input linguistic variables, the output linguistic variable, their domain values and linguistic terms.**

Variable name	Type of variable/ variable coding	Domain values	Linguistic terms
Vibrations amplitude along with the X-axis	Input/ $x_1 = A_X$	[145.11, 155.76] mm/s rms	$LT_{11}^{X_V} = A_X small$ $LT_{12}^{X_V} = A_X medium$ $LT_{13}^{X_V} = A_X big$
Vibrations amplitude along with the Y-axis	Input/ $x_2 = A_Y$	[7.81, 20.05] mm/s rms	$LT_{21}^{X_V} = A_Y small$ $LT_{22}^{X_V} = A_Y medium$ $LT_{23}^{X_V} = A_Y big$
Vibrations amplitude along with the Y-axis	Input/ $x_3 = A_Z$	[16.28, 22.47] mm/s rms	$LT_{31}^{X_V} = A_Z small$ $LT_{32}^{X_V} = A_Z medium$ $LT_{33}^{X_V} = A_Z big$
Abrasion resistance using the Martindale abrasion tester	Output/ $y_c = ARM$	[25104, 65000] Martindale cycles	$LT_1^{ARM} = ARMverysmall$ $LT_2^{ARM} = ARMsmall$ $LT_3^{ARM} = ARMmedium$ $LT_4^{ARM} = ARMbig$ $LT_5^{ARM} = ARMverybig$

The triangular and trapezoidal membership functions have been employed in most reliability and maintenance applications based on their simplicity and adequacy on realistic reflecting and modeling the uncertainty [59]–[61]. Nevertheless, recent studies indicate the Gaussian membership function as an appropriate membership function for the input variables in condition monitoring [62], [63]. Therefore, three fuzzy decision systems were built, using the triangular, trapezoidal and Gaussian membership functions for the input linguistic variables $X_V = \{A_X, A_Y, A_Z\}$. However, a triangular membership function was employed to express the membership function of the output linguistic variable y_c = ARM in each case.

The fuzzy rules base consisted of 27 rules, as follows:

$$\begin{aligned}
&FIR_1\text{: IF}(A_X = A_X\text{small AND } A_Y = A_Y\text{small}\\
&\text{AND}A_Z = A_Z\text{medium)THEN(ARM} = \text{ARMbig)}\\
&\ldots.\\
&FIR_{27}\text{:}(A_X = A_X\text{big AND } A_Y = A_Y\text{big AND}\\
&A_Z = A_Z\text{medium)THEN(ARM} = \text{ARMverysmall)}
\end{aligned} \tag{10}$$

The centroid method was used as the defuzzification method. The Fuzzy Logic Toolbox™of the Matlab ® software was used in order to develop each fuzzy decision system based on the estimation of the technical state of the textile machine. Figure 10 depicts the inference rules of the fuzzy decision system that employed the Gaussian membership functions for the three input linguistic variables.

Considering the amplitude of vibrations measured along with the three axes of a Cartesian coordinate system at one moment, the value of the ARM can be obtained through each fuzzy decision system. Then, it can be verified if ARM is within the limits of [25104, 65000] Martindale cycles. In the end, a decision regarding the state of the textile machine that operates with that particular needle (good/failure condition) can be taken and appropriate maintenance activities can be planned if is the case.

On the other hand, a relatively long time is requested for the Martindale test (it may usually take more than half a day). Therefore, the validation of each fuzzy decision system was performed considering the new and defective needles and another three cases in which needles with different degrees of wear were used. The results of the validation process are illustrated in Table 6.

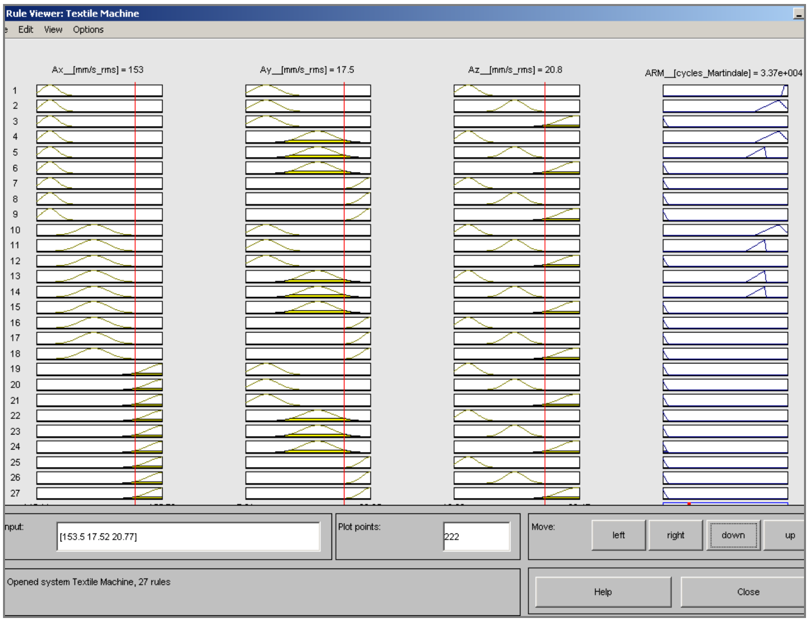


FIGURE 10. The inference rules of the fuzzy decision system that used the Gaussian membership functions for the input linguistic variables.

TABLE 6. The validation of the fuzzy decision systems.

No.	Amplitude of vibration (mm/s rms)			AMR_{pk} (Martindale cycles)						AMR_{ok} (Martindale cycles)
				Membership functions for the input linguistic variables (Tri-triangular, Trap-trapezoidal, Gauss-Gaussian)						
	A_X	A_Y	A_Z	Tri	Mdm*	Trap	Mdm*	Gauss	Mdm*	
1	145.11	7.81	16.28	63733	1	63498	1	64182	1	65000
2	149.40	10.80	18.05	55016	1	56197	1	59066	1	60212
3	151.44	14.67	19.33	52520	1	54878	1	55506	1	53488
4	153.81	17.05	20.59	35049	1	32178	1	31465	1	32668
5	155.76	20.05	22.47	27051	1	26379	1	25547	1	25104

* Maintenance decision-making: 1-good state and usable/ 2- failure state and maintenance needed

The performance of each fuzzy decision system was estimated using the MAPE and RMSPE scale-independent measures. Their expressions are as follows [64]:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\left|\frac{\mathrm{AMR_{ok}} - \mathrm{AMR_{pk}}}{\mathrm{AMR_{ok}}}\right| \tag{11}$$

and

$$\mathrm{RMSPE} = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\frac{\mathrm{AMR_{ok}} - \mathrm{AMR_{pk}}}{\mathrm{AMR_{ok}}}\right)^2} \tag{12}$$

where $\mathrm{AMR_p}$k and $\mathrm{AMR_{ok}}$ are the predicted and measured value of the ARM, respectively and $k = \overline{1,5}$. Table 7 depicts the values of MAPE and RMSPE for the three fuzzy decision systems. The lowest value of the RMSE and RMSPE were found equal to 2.47% and 2.68 %, respectively for the fuzzy decision system that used Gaussian membership functions for the input linguistic variables. Moreover, the values of the RMSE and RMSPE for all three cases are less than 10%, pointing out that the knowledge-based approach based on fuzzy logic and vibration monitoring demonstrates satisfactory performance.

TABLE 7. Comparison of the fuzzy decision systems.

Membership functions for the input linguistic variables					
Triangular		Trapezoidal		Gaussian	
MAPE [%]	RMSPE [%]	MAPE [%]	RMSPE [%]	MAPE [%]	RMSPE [%]
5.48	6.24	3.63	4.11	2.47	2.68

IV. CONCLUSION

With proper design and implementation, condition-based maintenance may be an effective tool for maintenance decision-making of industrial machines. Since the condition monitoring has no universal application, specific approaches must be employed according to the characteristics of the machines of interest. Textile machines are systems with rotating and reciprocating components operating at relatively high-speed, and therefore a vibration monitoring was proposed to detect their failure development. Since the manufacturers of textile machines do not specify the admissible level of vibrations during the function of their machines, an operating regime at which vibrations are at lowest levels can also be recommended based on vibration monitoring.

A mathematical representation of the degradation phenomenon of textile machines is difficult to be determined because of its complexity and nonlinearity. Therefore, the characterization of the degradation phenomenon of textile machines involves some degree of uncertainty and vagueness and a knowledge-based approach based on fuzzy logic may be employed to overcome such difficulties. However, research on using fuzzy logic in the condition-based maintenance of textile machines is still less explored. Within this context, a maintenance decision-making support has been developed for textile machines considering a knowledge-based approach that used fuzzy logic and vibration monitoring. The effectiveness of the proposed approach was investigated for an overlock sewing machine. The results demonstrate satisfactory performance, indicating that such an approach can be used for decision making about the maintenance of textile machines.

At the same time, the existing literature shows that different combinations of soft computing and other artificial intelligence techniques may be employed in maintenance decision-making support [22], [24], [38], [65]. Therefore, they are also considered as important research topics for textile machines and future studies are expected to confirm whether such combinations are more effective in supporting maintenance decision-making of these machines.

REFERENCES

[1] I. Alsyouf, "Maintenance practices in Swedish industries: Survey results," *Int. J. Prod. Econ.*, vol. 121, no. 1, pp. 212–223, Sep. 2009.

[2] S. H. Huang, J. P. Dismukes, A. Mousalam, R. B. Razzak, and D. E. Robinson, "Manufacturing productivity improvement using effectiveness metrics and simulation analysis," *Int. J. Prod. Res.*, vol. 41, no. 3, pp. 513–527, 2003.

[3] B. Al-Najjar, "The lack of maintenance and not maintenance which costs: A model to describe and quantify the impact of vibration-based maintenance on company's business," *Int. J. Prod. Econ.*, vol. 107, no. 1, pp. 260–273, May 2007.

[4] I. Alsyouf, "The role of maintenance in improving companies' productivity and profitability," *Int. J. Prod. Econ.*, vol. 105, no. 1, pp. 70–78, Jan. 2007.

[5] A. Houshyar, "Reliability and maintainability of machinery and equipment, part 1: Accessibility and assessing machine tool R&M performance," *Int. J. Model. Simul.*, vol. 24, no. 4, pp. 201–210, 2004.

[6] J. T. Luxhøj, J. O. Riis, and U. Thorsteinsson, "Trends and perspectives in industrial maintenance management," *J. Manuf. Syst.*, vol. 16, no. 6, pp. 437–453, 1997.

[7] S. O. Duffuaa and S. Raouf, *Planning and Control of Maintenance Systems: Modelling and Analysis*, 2nd ed. Cham, Switzerland: Springer, 2015.

[8] R. Kothamasu, S. H. Huang, and W. H. VerDuin, "System health monitoring and prognostics—A review of current paradigms and practices," *Int. J. Adv. Manuf. Technol.*, vol. 28, nos. 9–10, pp. 1012–1024, Jul. 2006.

[9] B. S. Dhillon, *Engineering Maintenance: A Modern Approach*. Boca Raton, FL, USA: CRC Press, 2002.

[10] A. H. C. Tsang, "Condition-based maintenance: Tools and decision making," *J. Qual. Maintenance Eng.*, vol. 1, no. 3, pp. 3–17, 1995.

[11] K.-F. Pun, K.-S. Chin, M.-F. Chow, and H. C. W. Lau, "An effectiveness-centred approach to maintenance management: A case study," *J. Qual. Maintenance Eng.*, vol. 8, no. 4, pp. 346–368, 2002.

[12] L. Swanson, "Linking maintenance strategies to performance," *Int. J. Prod. Econ.*, vol. 70, no. 3, pp. 237–244, Apr. 2001.

[13] E. Bottani, G. Ferretti, R. Montanari, and G. Vignali, "An empirical study on the relationships between maintenance policies and approaches among Italian companies," *J. Qual. Maintenance Eng.*, vol. 20, no. 2, pp. 135–162, 2014.

[14] M. Rausand and A. Høyland, *System Reliability Theory: Models, Statistical Methods, and Applications*, 2nd ed. Hoboken, NJ, USA: Wiley, 2004.

[15] R. Jiang, P. Ji, and A. H. C. Tsang, "Preventive effect of optimal replacement policies," *J. Qual. Maintenance Eng.*, vol. 12, no. 3, pp. 267–274, 2006.

[16] R. Ahmad and S. Kamaruddin, "An overview of time-based and condition-based maintenance in industrial application," *Comput. Ind. Eng.*, vol. 63, no. 1, pp. 135–149, Aug. 2012.

[17] R. Dekker, "Applications of maintenance optimization models: A review and analysis," *Rel. Eng. Syst. Saf.*, vol. 51, no. 3, pp. 229–240, Mar. 1996.

[18] H. P. Bloch and F. K. Geitner, *Machinery Failure Analysis and Troubleshooting*, vol. 2, 3rd ed. Houston, TX, USA: Gulf Publishing, 1999.

[19] R. Ahmad and S. Kamaruddin, "A review of condition-based maintenance decision-making," *Eur. J. Ind. Eng.*, vol. 6, no. 5, pp. 519–541, 2012.

[20] R. B. Chinnam and P. Baruah, "A neuro-fuzzy approach for estimating mean residual life in condition-based maintenance systems," *Int. J. Mater. Product Technol.*, vol. 20, nos. 1–3, pp. 166–179, 2004.

[21] H. M. Hashemian and W. C. Bean, "State-of-the-art predictive maintenance techniques," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 10, pp. 3480–3492, Oct. 2011.

[22] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mech. Syst. Signal Process.*, vol. 20, no. 7, pp. 1483–1510, Oct. 2006.

[23] A. Heng, S. Zhang, A. C. C. Tan, and J. Mathew, "Rotating machinery prognostics: State of the art, challenges and opportunities," *Mech. Syst. Signal Process.*, vol. 23, no. 3, pp. 724–739, Apr. 2009.

[24] Y. Peng, M. Dong, and M. J. Zuo, "Current status of machine prognostics in condition-based maintenance: A review," *Int. J. Adv. Manuf. Technol.*, vol. 50, nos. 1–4, pp. 297–313, Sep. 2010.

[25] J.-H. Shin and H.-B. Jun, "On condition based maintenance policy," *J. Comput. Des. Eng.*, vol. 2, no. 2, pp. 119–127, Apr. 2015.

[26] J. M. Sharp, "Condition monitoring of key elements in high speed textile machinery," in *Condition Monitoring and Diagnostic Engineering Management*, R. B. K. N. Rao, J. Au, and B. Griffiths, Eds. Dordrecht, The Netherlands: Springer, 1990, pp. 142–147.

[27] F. Cloppenburg, V. Niebel, and T. Gries, "Systematic development of condition monitoring and self-optimisation for production machines for textiles using sensor systems," *Unitex*, no. 4, pp. 14–16, Dec. 2015.

[28] A. Wolfram and R. Isermann, "Component based tele-diagnosis approach to a textile machine," *Control Eng. Pract.*, vol. 10, pp. 1251–1257, Nov. 2002.

[29] A. Scarpellini, L. Fasanotti, A. Piccinini, S. Ierace, and F. Floreani, "A Web-based monitoring application for textile machinery industry," in *Proc. IEEE 2nd Int. Forum Res. Technol. Soc. Ind. Leveraging Better Tomorrow (RTSI)*, Bologna, Italy, Sep. 2016, pp. 1–6.

[30] R. K. Mobley, *An Introduction to Predictive Maintenance*, 2nd ed. London, U.K.: Butterworth, 2002.

[31] R. B. Randall, *Vibration-based Condition Monitoring: Industrial, Aerospace and Automotive Applications*, Chichester, U.K.: Wiley, 2011.

[32] K. N. Gupta, "Vibration—A tool for machine diagnostics and condition monitoring," *Sadhana*, vol. 22, no. 3, pp. 393–410, Jun. 1997.

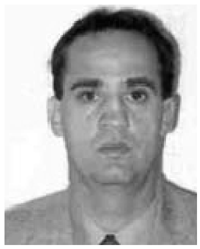
[33] D. Goyal and B. S. Pabla, "Condition based maintenance of machine tools—A review," *CIRP J. Manuf. Sci. Technol.*, vol. 10, pp. 24–35, Aug. 2015.

[34] D. Goyal and B. S. Pabla, "The vibration monitoring methods and signal processing techniques for structural health monitoring: A review," *Arch. Comput. Methods Eng.*, vol. 23, no. 4, pp. 585–594, Dec. 2016.

[35] M. Şuteu, L. Indrie, M. Baidoc, and M. Ganea, "Determining the optimal operating mode for the embroidery machine by using the vibration measurement technique," *Ind. Textila*, vol. 65, no. 1, pp. 17–21, 2014.

[36] S. Durrleman and R. Simon, "Flexible regression models with cubic splines," *Statist. Med.*, vol. 8, pp. 551–561, May 1989.

[37] A. Bousdekis, B. Magoutas, D. Apostolou, and G. Mentzas, "A proactive decision making framework for condition-based maintenance," *Ind. Manage. Data Syst.*, vol. 115, no. 7, pp. 1225–1250, 2015.
[38] H. M. Elattar, H. K. Elminir, and A. M. Riad, "Prognostics: A literature review," *Complex Intell. Syst.*, vol. 2, no. 2, pp. 125–154, Jun. 2016.
[39] G. Vachtsevanos, F. L. Lewis, M. Roemer, A. Hess, and B. Wu, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*. Hoboken, NJ, USA: Wiley, 2006.
[40] J. Campos, "Development in the application of ICT in condition monitoring and maintenance," *Comput. Ind.*, vol. 60, no. 1, pp. 1–20, Jan. 2009.
[41] R. R. Da Silva, E. D. S. Costa, R. C. L. De Oliveira, and A. L. A. Mesquita, "Fault diagnosis in rotating machine using full spectrum of vibration and fuzzy logic," *J. Eng. Sci. Technol.*, vol. 12, no. 11, pp. 2952–2964, Jan. 2017.
[42] R. F. M. Marçal, K. Hatakeyama, and D. J. Czelusniak, "Expert System based on Fuzzy rules for monitoring and diagnosis of operation conditions in rotating machines," *Adv. Mater. Res.*, vols. 1061–1062, pp. 950–960, Dec. 2015.
[43] H. Wang and P. Chen, "Fuzzy diagnosis method for rotating machinery in variable rotating speed," *IEEE Sensors J.*, vol. 11, no. 1, pp. 23–34, Jan. 2011.
[44] H. Liang, S. Cao, X. Li, and H. Xiang, "Design of the remote fault diagnosis system for the printing machines based on the Internet of Things and fuzzy inference," in *Advanced Graphic Communications and Media Technologies* (Lecture Notes in Electrical Engineering), vol. 417, P. Zhao, Y. Ouyang, M. Xu, L. Yang, and Y. Ouyang, Eds. Singapore: Springer, 2017, pp. 825–835.
[45] D. Skarlatos, K. Karakasis, and A. Trochidis, "Railway wheel fault diagnosis using a fuzzy-logic method," *Appl. Acoust.*, vol. 65, no. 10, pp. 951–966, Oct. 2004.
[46] A. Azadeh, V. Ebrahimipour, and P. Bavar, "A fuzzy inference system for pump failure diagnosis to improve maintenance process: The case of a petrochemical industry," *Expert Syst. Appl.*, vol. 37, no. 1, pp. 627–639, Jan. 2010.
[47] S. Hussain, "Fuzzy information system for condition based maintenance of gearbox," *J. Intell. Fuzzy Syst.*, vol. 28, no. 6, pp. 2509–2518, 2015.
[48] M. Cerrada, C. Li, R.-V. Sánchez, F. Pacheco, D. Cabrera, and J. V. de Oliveira, "A fuzzy transition based approach for fault severity prediction in helical gearboxes," *Fuzzy Sets Syst.*, vol. 337, pp. 52–73, Apr. 2018.
[49] N. Vafaei, R. A. Ribeiro, and L. M. Camarinha-Matos, "Fuzzy early warning systems for condition based maintenance," *Comput. Ind. Eng.*, vol. 128, pp. 736–746, Feb. 2019.
[50] S. M. Darwish, "Soft computing applied to the build of textile defects inspection system," *IET Comput. Vis.*, vol. 7, no. 5, pp. 373–381, Oct. 2013.
[51] R. Guruprasad and B. K. Behera, "Soft computing in textiles," *Indian J. Fibre Textile Res.*, vol. 35, pp. 75–84, Mar. 2010.
[52] A. Majumdar, Ed. *Soft Computing in Textile Engineering* (Woodhead Publishing Series in Textiles), vol. 111. Cambridge, U.K.: Woodhead Publishing Limited, 2011.
[53] L. M. Sztandera and C. Pastore, Eds., *Soft Computing in Textile Sciences*. Berlin, Germany: Springer-Verlag, 2003.
[54] M. Baban, C. F. Baban, and F. S. Blaga, "Maintenance planning of cold plastic deformation tools using fuzzy logic," *Eksploatacja Niezawodnosc-Maintenance Rel.*, vol. 3, pp. 21–26, Jan. 2010.
[55] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Upper Saddle River, NJ, USA: Prentice-Hall, 1997.
[56] C. W. de Silva, *Intelligent Control: Fuzzy Logic Applications*. Boca Raton, FL, USA: CRC Press, 1995.
[57] N. Özdil, G. Kayseri, and G. S. Mengüç, "Analysis of abrasion characteristics in textiles," in *Abrasion Resistance of Materials*, M. Adamiak, Ed. Rijeka, Croatia: InTech, 2012, pp. 119–146.
[58] J. Maindonald and W. J. Braun, *Data Analysis and Graphics Using R: An Example-Based Approach*. Cambridge, U.K.: Cambridge Univ. Press, 2003.
[59] A. O. Esogbue and W. E. Hearnes, II, "Maintenance and replacement models under a fuzzy framework," in *Fuzzy Sets in Decision Analysis, Operations Research and Statistics*, R. Siowinski, Ed. New York, NY, USA: Springer, 1998, pp. 421–447.
[60] H. C. W. Lau and R. A. Dwight, "A fuzzy-based decision support model for engineering asset condition monitoring—A case study of examination of water pipelines," *Expert Syst. Appl.*, vol. 38, no. 10, pp. 13342–13350, Sep. 2011.
[61] J. H. Purba, J. Lu, G. Zhang, and W. Pedrycz, "A fuzzy reliability assessment of basic events of fault trees through qualitative data processing," *Fuzzy Sets Syst.*, vol. 243, pp. 50–69, May 2014.
[62] T. Berredjem and M. Benidir, "Bearing faults diagnosis using fuzzy expert system relying on an improved range overlaps and similarity method," *Expert Syst. Appl.*, vol. 108, pp. 134–142, Oct. 2018.
[63] B. Cuka and D.-W. Kim, "Fuzzy logic based tool condition monitoring for end-milling," *Robot. Comput.-Integr. Manuf.*, vol. 47, pp. 22–36, Oct. 2017.
[64] R. J. Hyndman and A. B. Koehler, "Another look at measures of forecast accuracy," *Int. J. Forecasting*, vol. 22, no. 4, pp. 679–688, Oct./Dec. 2006.
[65] D. Goyal, B. S. Pabla, S. S. Dhami, and K. Lachhwani, "Optimization of condition-based maintenance using soft computing," *Neural Comput. Appl.*, vol. 28, pp. 829–844, Dec. 2017.



MARIUS BĂBAN received the Ph.D. degree in electronics engineering and telecommunication from the University Politehnica of Bucharest, in 2002, and the Habilitation degree in engineering and management from the Lucian Blaga University of Sibiu, in 2016. Since 2009, he has been a Professor with the Faculty of Management and Technological Engineering, University of Oradea. He is also a Ph.D. Advisor with the University of Oradea. His research interests include the data acquisition for the diagnosis of technical systems and their reliability modeling, and maintenance planning through the use of soft computing.

CĂLIN FLORIN BĂBAN received the Ph.D. degree in reliability from the Politehnica University of Bucharest, in 1998, and the Habilitation degree in engineering and management, in 2015. He is currently Professor with the Faculty of Management and Technological Engineering, University of Oradea, in 2004, where he is also a Ph.D. Advisor in engineering and management. His areas of interest include data management and soft computing in engineering applications.

MARIUS DARIUS ŞUTEU received the Ph.D. degree in industrial engineering from the University of Oradea, in 2013, where he is currently a Lecturer with the Department of Engineering and Industrial Management in Textiles and Leatherwork. His current research interests include the diagnosis, condition monitoring, and the condition-based maintenance of textile machines.